Does EigenPalm work? A System and Evaluation Perspective

[1]King-Hong Cheung, [1,2]Adams Kong, [1]David Zhang, [2]Mohamed Kamel and [1]Jane You

[1]*Department of Computing, The Hong Kong Polytechnic University, Hung Hom, Hong Kong*
{cskhc, cswkkong, csdzhang, csyjia} @comp.polyu.edu.hk
[2]*Pattern Analysis and Machine Intelligence Lab, University of Waterloo,*
200 University Avenue West, Waterloo, Ontario, N2L 3G1, Canada
adamskong@ieee.org, mkamel@uwaterloo.ca

Abstract

Recently, there are keen interests in EigenPalm, which, collectively, refers to those methods that extract palmprint features directly from the appearance by means of Principal Component Analysis (PCA) for (dis)similarity matching. Encouraging results have been reported with the use of EigenPalm. However, we find a different story under a system and evaluation perspective. In this paper, we would like to introduce three issues that should be considered: the effects of templates from two different sessions, the effects of identical twins and the effects of unseen subjects. They are missing in the previous studies of EigenPalm.

1. Introduction

Palmprint has been a member of the biometrics for personal authentication for more than eight years. Various techniques have been proposed for palmprint recognition [6][8][2][3]. Several biometric fusion approaches involving palmprints have also been proposed [9][1].

Recently, there are keen interests in EigenPalm [2][1][3]. We use EigenPalm to collectively refer to the methods that extract palmprint features directly from the appearance by means of Principal Component Analysis for *Personal Identification*. We use ROI to refer to the Region of Interests of a palmprint (sub-)image used for feature extraction.

Principal Component Analysis (PCA), which is also known as (discrete) Karhunen-Loève (K-L) Transform or Hotelling Transform, is a statistical method that linearly maps the data space (original distribution) to the feature space (usually a subspace of the original) with minimal mean square (approximation) error. Since PCA has been applied in many application areas, we are not going to review the mathematical formulations here. Please refer to [7] and [2] for the mathematical details. One well-known application is in face recognition known as Eigenface [7].

Several studies have reported high recognition accuracy using EigenPalm [2][3][1], e.g. 99.149% in Ref. [2]. Some reported results, however, cannot be obtained in real applications since the tested palmprints were collected from the same time. There are three issues that have not been addressed properly in the previous studies [2][3][1]: the effects of palmprints from two different sessions, the effects of identical twins and the effects of unseen subjects. Biometric systems, which fail to sustain acceptable performance in different sessions, cannot be put into practical use. If biometric systems cannot cope with identical twins, they have potential security problems [5]. Finally, if biometric systems cannot deals with unseen impostors, they may not be used in an open environment.

The aim of this paper is to give a complete performance evaluation for the use of EigenPalm in real applications. Our paper is organized as follows. Section 2 gives a brief review of current works in EigenPalm. Section 3 describes the three issues in system and evaluation perspective. Section 4 presents the details and results of tests on EigenPalm. Section 5 concludes our paper.

2. Current Works

Lu et al. [2] are among the first to propose the use of PCA in the palmprint recognition. In their experiments, each user provided two to four images for registration and the size of ROI was 128×128. They reported remarkably high recognition accuracy but they did not state whether all the templates were in one, same session.

Connie et al. [3] gave a detailed analysis on the subspace methods, PCA, FDA and ICA, for palmprint recognition. They collected palmprints from subjects in two sessions and their ROI was of size 150×150. They

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used half of each palm's templates for database plus training and another half for testing but they did not state the composition of the two halves.

Ribaric and Fratic [1] adopted EigenPalm and fused with Eigenfinger at score level for better personal identification. They reported the performance of EigenPalm as the partial result of their whole report. Their ROI was of size, 64×64. In their database, palmprints of some users were collected in one session while some were collected in two different sessions. They divided the database into the three subject groups (see Section 3 for the details). Although they addressed the effect of unseen subjects, they did not clearly state: 1) who provided palmprints in one session and who provided palmprints in two sessions; 2) the composition of subjects in 1) in the subject groups.

Jing and Zhang [9] implemented EigenPalm for their comparison. Their database is a subset of ours. They used the first five (right hand) palmprints with ROI of size 64×64 as the gallery and the training set for PCA. Notably, they mixed the palmprints of the two different sessions into the query set.

All studies mentioned above have not properly addressed the effect of different sessions and identical twins. Ribaric and Fratic is the only one who has considered the effect of unseen subjects.

3. A system evaluation framework

In this section, we will layout the framework that has been used to perform the evaluation afterwards. We have identified three major issues subject to tests, which will be presented in the following subsections.

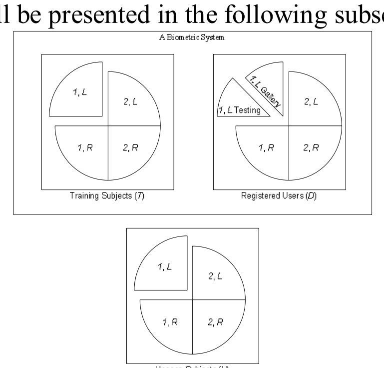

Figure 1 An illustration of the three subject groups and their templates

Evaluating a biometric system, three groups of subjects are of interests, namely, Registered Users (*D*), Training subjects (*T*), Unseen Subjects (*U*). Registered users are subjects who will use the system and their templates will be stored in the system (gallery). (see Figure 1) In *enrollment*, biometric templates of registered users are constructed. Later, registered users will present their biometrics (query/probe) to the system for authentication. Therefore, the matching has to be performed on the templates from two different sessions. In order to simulate this situation, we should test a biometric system with templates from two (or more) different sessions. We use *1* and *2* to notate the sets of templates from the first and second session respectively. In the case of palmprint, each sound person have two palms, the left (*L*) and the right (*R*).

To represent a template, we define, $I_j^i(g, s, h)$, where i represents the template identity, j is the subject identity, $g \in \{D, U, T\}$ is the group which subject j belongs, and $s \in \{1, 2\}$ represents the session and $h \in \{L, R\}$ represents the palm from which the template is obtained. All cases of matchings are summarized in Table 1 and are presented in the following subsections.

3.1 Matching with Two Sessions or more

Templates of registered users are collected at the enrollment and stored in the system (gallery). Biometric templates to be matched against those in gallery are obtained at a different date or time. In order to provide a realistic and objective system evaluation, matching templates from two different sessions or more is suggested. If, however, the gallery contains some templates collected at the same time as the query ones, the evaluation may not reflect the actual system performance, especially for learning methods, e.g. PCA. Therefore, a query should contain only the templates from one session other the gallery.

Case 1: Matchings M1-M4 given in Table 1 are *general genuine matchings*.

Case 2: Matchings M5-M8 given in Table 1 are *general impostor matchings*.

3.2 Matching with Identical Twins

Identical twins grow out of the same Deoxyribo Nucleic Acid (DNA). Although they account for a small portion of the total population, it is a hole in the security of biometric systems if this is not properly addressed. [5]

In practice, it is difficult to collect biometric templates from a large number of identical twins. We can, nevertheless, collect palmprints from subjects that grow out of the same DNA: the left and right palms of sound people. We can mirror the right to match against the left and vice versa. We refer these as *virtual twins*.

Case 3: Matchings M9-M16 given in Table 1 are (*virtual*) *twins impostor matchings*.

A *side impostor matching* differs from the general one (Case 2) that the matching performs on the palmprints from the palms of the same side. Some researchers [6][2][3] treat the left and right palms (without mirroring) of one person as different palm classes when they do the matching. We distinguish these two kinds of impostor matching hereafter.

Case 4: Matchings M17-M24 given in Table 1 are *side impostor matchings*.

3.3 Matching with Unseen Subjects

In practice, many biometric systems are installed in an open environment. Potential impostors are non-registered users. Gibbons et al. [4] have studied evaluation in open systems, i.e. the effects of non-members (referred as unseen subjects in this paper, $D \cap U$ = NULL). They found the accuracy reported for closed systems may not be generalized to open systems. Therefore, biometric systems are subjected to test on this issue.

Case 5: Matchings M25-M32 given in Table 1 are *unseen impostor matchings*.

4. Experimental Results

We will give the system performance of EigenPalm under the evaluation framework presented in Section 3 above. It is worth to note that we are reporting the Genuine Acceptance Rate (GAR, which is the complement of False Reject Rate, FRR) against Impostor Acceptance Rate (IAR, also known as False Acceptance Rate, FAR) in the form of Receiver Operating Characteristics (ROC) curves.

The palmprint database used in this paper is part of the database created in [6]. It contains palmprint images from 190 subjects. Each subject provided around 10 palmprint images from each palm at two different occasions. The size of the preprocessed images is 128 by 128. (see [6] for the details of palmprint preprocessing) Our ROI is obtained by resizing the preprocessed images from 128×128 to 64×64 using bicubic interpolation.

We randomly divide the subjects into the three groups: 70 subjects are registered users, 30 subjects are unseen subjects and 90 subjects are training subjects. We separate registered and training subjects in our tests since EigenPalm is a class independent learning method. In real applications, the number of registered users may not be sufficient to train the EigenPalms.

To compensate the sensor variations between the two capture sessions, we normalize both the mean and variance of the intensity of the ROIs to 100 as in Ref. [10]. The first one hundred PCA coefficients are used to form the feature vector, i.e. feature dimension is 100 because it is reported to be the best [2] and we do not observe significant difference of using higher feature dimensions as in [1]. Euclidean distance (L_2) is the (dis)similarity measure in our tests. Figure 2 shows a sample palmprint in our database and the first three principal components learned from training subjects.

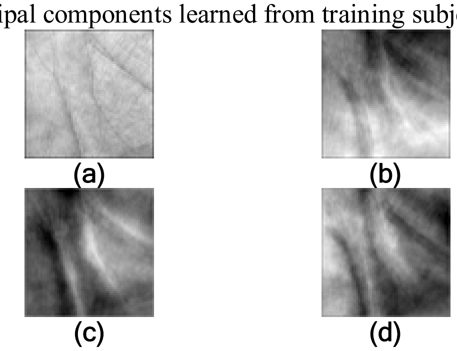

Figure 2. (a) a sample palmprint template and (b)-(d) the first three principal components of trained templates, $I_j^i(T, 1, L)$

Without loss of generality, we report only the result of M1, M3, M9, M13, M17, M21, M25 and M29. We use the first five palmprints $\{I_j^i(D, 1, L) \mid i = 1\ldots5, \forall j \in D\}$ as the gallery throughout the tests. For Matchings M1 and M17, we use $\{I_j^i(D, 1, L) \mid i \neq 1\ldots5, \forall j \in D\}$ as the query set.

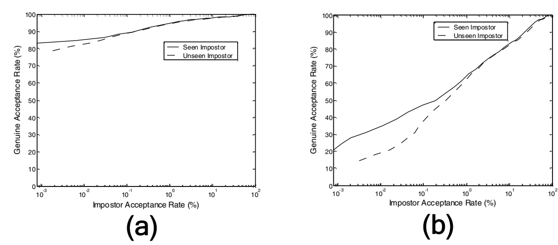

Figure 3. ROC curves of General Matching (a) same session and (b) different session matching

To show the difference in performance, we match palmprints from the same sessions and the different sessions. For matching of the same session, number of comparisons of genuine (M1), side impostor (M17) and unseen impostor (M25) are 1,805, 126,190 and 217,664 respectively. For matching of the different sessions, number of comparisons of genuine (M3), side impostor (M21) and unseen impostor (M29) are 3,505, 241,790 and 215,516 respectively. Their ROC curves are given in Figures 3 and 4. From Figures 3 and 4, we can see good performance in the same session matching but there is a huge drop in the different sessions matching. This drop has not been reported in the previous EigenPalm studies [2][3][1].

In the test of the effect of twins on EigenPalm, the numbers of comparisons of genuine and side impostor are the same as in the above test. Number of comparisons of (virtual) twins impostor in the same session (M9) is 3,555 while in the different session (M13) is 3,500. From Figure 3, we can observe significant performance degradation due to virtual twins matching, especially when it is matching in different sessions.

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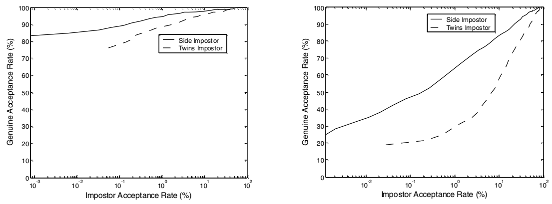

Figure 4. ROC curves of (Virtual) Twins Matching (a) same session and (b) different session matching

In the test of the effect of unseen subjects on EigenPalm, from Figure 3, the performance degradation at small FAR is relatively slight compared to the drop due to the effect of different sessions.

Table 1. Summary of various types of matchings

	Gallery $I_j^i(g, s, h)$			Query $I_n^m(g, s, h)$			Case and Conditions
	(g)	(s)	(h)	(g)	(s)	(h)	
M1*	D	1	L/R	D	1	L/R	1. $j = n$ and, I_j^i and I_n^m are from the same palm
M2*	D	2	L/R	D	2	L/R	
M3	D	1	L/R	D	2	L/R	
M4	D	2	L/R	D	1	L/R	
M5*	D	1	L/R	D	1	L/R	2. $j \neq n$ or I_j^i and I_n^m are from the different palm
M6*	D	2	L/R	D	2	L/R	
M7	D	1	L/R	D	2	L/R	
M8	D	2	L/R	D	1	L/R	
M9	D	1	L	D	1	R'	3. $j = n$ and, L' and R' are the mirrored palmprint templates
M10	D	1	R	D	1	L'	
M11	D	2	L	D	2	R'	
M12	D	2	R	D	2	L'	
M13	D	1	L	D	2	R'	
M14	D	1	R	D	2	L'	
M15	D	2	L	D	1	R'	
M16	D	2	R	D	1	L'	
M17*	D	1	L	D	1	L	4. $j \neq n$
M18*	D	1	R	D	1	R	
M19*	D	2	L	D	2	L	
M20*	D	2	R	D	2	R	
M21	D	1	L	D	2	L	
M21	D	1	R	D	2	R	
M23	D	2	L	D	1	L	
M24	D	2	R	D	1	R	
M25	D	1	L	U	1	L	5. $D \cap U$ = NULL
M26	D	1	R	U	1	R	
M27	D	2	L	U	2	L	
M28	D	2	R	U	2	R	
M29	D	1	L	U	2	L	
M30	D	1	R	U	2	R	
M31	D	2	L	U	1	L	
M32	D	2	R	U	1	R	

*The query set of matchings, which is the complement of the gallery, is marked "Testing" in Figure 1.

5. Conclusions

We have briefly reviewed the current works in EigenPalm and pointed out three issues, including different sessions matching, twins matching and unseen subjects matching. We present a standardized evaluation framework for biometric evaluations and systematically evaluate EigenPalm based on the framework. We discover that EigenPalm is not effective for real applications since its performance is relatively low when the palmprints are collected from different time. It is contrast to the impressive results reported in the previous studies [2][3][1].

We also discover the performance drop in twin matchings. It should note that the first few principal components of EigenPalm extract the principal lines as features, which are genetically dependant [5].

Lastly, we observe the performance degradation due to unseen subjects; it is relatively slight comparing to that due to the different sessions. Thus, according to our experiments, we are unfavorable to EigenPalm's performance and its use in high security systems.

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